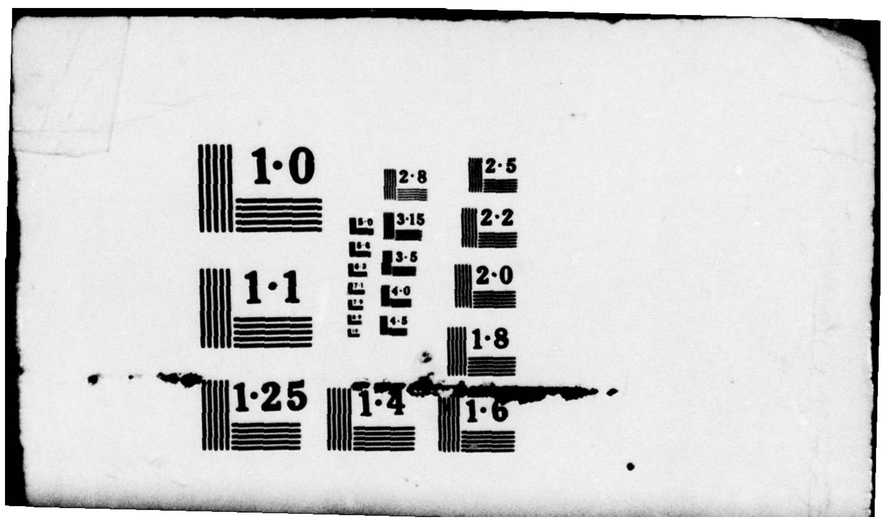
AD-A072 838 WISCONSIN UNIV-MILWAUKEE DEPT OF SYSTEMS DESIGN F/G 5/8
SOME MODELS OF HUMAN ERROR FOR MAN-MACHINE SYSTEM EVALUATION.(U)
MAY 79 M U THOMAS N00014-77-C-0587
UNCLASSIFIED TR-79-5 NL

1 OF 1
AD
A072838

END
DATE
FILMED
9 79
DDC


1·0
2·8
2·5
3·15
2·2
3·5
1·1
2·0
4·0
4·5
1·8
1·25
1·4
1·6

LEVEL II

(12) B.S.

(15) Report N00014-77-C-0587

AD A072838

(6) SOME MODELS OF HUMAN ERROR FOR MAN-MACHINE SYSTEM EVALUATION

(9) Final Technical Report No. (14) TR-79-5

1 Jul 77-30 Dec 78

(10) Marlin U. Thomas

Technical Analysis and Planning
Chrysler Corporation
P. O. Box 1919
Detroit, Michigan 48288

and

University of Michigan
Department of Industrial & Operations
Engineering
231 W. Engineering
Ann Arbor, Michigan 48109

(12) 32p.

(11) 15 May 1979

A Final Report for Period: 1 July 1977 - 30 December 1978

Approved for public release; distribution unlimited

Wisconsin Univ- Milwaukee
Dept. of Systems Design

411339

Prepared for:
OFFICE OF NAVAL RESEARCH
Code 431
Arlington, Virginia 22217

79 08 15 008

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER N00014-77-C-0587	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Some Models of Human Error for Man-Machine System Evaluation		5. TYPE OF REPORT & PERIOD COVERED Final 1 July 1977 - 30 December 78
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Marlin U. Thomas Chrysler Corporation and University of Michigan		8. CONTRACT OR GRANT NUMBER(s) N00014-77-C-0587 New
9. PERFORMING ORGANIZATION NAME AND ADDRESS The University of Wisconsin - Milwaukee Systems Design Department P.O. Box 784 - Milwaukee, WI 53201		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research Code 431 Arlington, Virginia 22217		12. REPORT DATE 15 May 1978
		13. NUMBER OF PAGES
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office) Office of Naval Research Branch Office Chicago 536 S. Clark Street Chicago, Illinois 60605		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Prepared in cooperation with the University of Michigan

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Man-machine system, man-machine linkage, human error, man-machine error models

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

A framework is presented for quantifying and modeling the occurance of human error events in a system. Decision tasks are classified according to the stochastic behavior of the relevant variables associated with the man-machine linkages. A general semi-Markov formulation is presented for describing transitions among error states. Closed form results for the time-between-errors are given through transform relationships for the case where interdecision times form a renewal process. An approximate

over

DD FORM 1473 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-014-6601

Unclassified
SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

79 08 15 008

time-between-error distribution is given that provides computational ease and compared well with some experimental data obtained from a laboratory human decision-making task.

Accession For	
NTIS GRA&I	✓
DDC TAB	
Unannounced	
Justification	
By	
Distribution/	
Availability Codes	
Dist	Avail and/or special
A	

SUMMARY

Human errors account for a significant portion of the overall effectiveness of many man-machine systems; particularly large scale command, control, and communication type systems that contain numerous man-machine linkages. Although considerable efforts to quantify and better understand human error performance have been extended and reported, a unified approach for incorporating error performance in system effectiveness measurement and assessments is lacking. A major difficulty that at least partially accounts for the lack of progress in this area is the lack of data. Since most of the errors pertaining to overall system effectiveness are typically rare events, histories are not generally available. These events are also usually very expensive when they do occur, however, thus providing the motivation to establish models for describing and studying various operational scenarios.

A framework for modeling human error performance is presented that includes a classification system based on the stochastic behavior of the relevant variables associated with the man-machine linkages. A semi-Markov formulation is presented for generalizing man-machine system performance and describing the transitions among various error states. As a special case we consider a human operator that commits an error with a constant probability at each randomly occuring decision point. The inter-decision times are assumed to form a renewal process and closed form results for the time-between-errors are given through transforms. So for the case where the inter-decision times are exponentially distributed, the time-between-errors is also exponential.

Other distributions, however, such as the commonly assumed Normal can be cumbersome. An approximate time-between-error distribution is developed that provides computational ease and only very broad assumptions are necessary. This approximation was applied to data from a laboratory human decision making task. Three operators performed the task with an average time-between-errors of 2326 msec and an average error probability of .051. The approximation provided relatively accurate, but consistently lower probability estimates than the experimental estimates.

Future direction is suggested in applications of the semi-Markov model. This includes multi-state renewal models and situations where the error probability at decision points is not constant throughout time. Man-in-the-loop simulation is suggested for further exploration of human error processes in complex man-machine environments.

ACKNOWLEDGEMENTS

This work was done while the author was Associate Professor of Systems Design at the University of Wisconsin - Milwaukee. He is grateful to the University of Michigan Department of Industrial and Operations Engineering for the preparation of this final report. Appreciation is also extended to Kim DeHenau for typing this manuscript.

TABLE OF CONTENTS

FIGURES

TABLES

1. INTRODUCTION

Performance quantification is a major problem in analyzing and evaluating man-machine systems, due primarily to the human elements involved. This is particularly true of the large scale command, control, and communication systems that have become vital to our military of today. These systems consist of large configurations of human operators interacting with computers and complex equipment in decision-making roles where they transform flows of information. The mental processing demands on the operators conducting monitoring and control type tasks in these environments are high and their performance can significantly influence the overall system effectiveness.

Until early 1960, most human performance studies except for vigilance emphasized the time prediction aspects of performance and indirectly suppressed or ignored errors. Military analysts then began to examine the impact of human errors on system effectiveness (Cooper [7], Meister [13]), which led to the development of a system for quantifying reliability in man-machine systems (Meister [14]). This system, analogous to the pre-determined motion time systems used for estimating task times, consists of a data base and a model for relating the various components of performance. Although this system has been refined and proven successful in numerous applications, it has the same drawbacks that the predetermined time prediction systems have in that a very extensive and detailed classification system is required and the data comes from highly diverse and variable sources. Mills and Hatfield [15] have reported on the relative difficulties in identifying predictive units as well as other problems with the

assumptions required in using a human performance reliability data base. Asken and Regulinski [3] have suggested an approach to quantifying human reliability that basically consists of drawing a direct correspondence to reliability concepts for physical components. Recent efforts at incorporating and dealing with human error performance in man-machine systems have been more situation specific. Lamb and Williams [10] examined the prediction of human operator performance for sonar maintenance functions. Dunlay and Horonjeff [8] developed an empirical model for predicting air traffic control conflicts using operator judgement error as a major performance measure. Feyock [9] devised a computer aided instruction procedure for improving the handling of errors in man-machine interfaces. While data availability is a problem in many applications, Apostolakis and Bansal [2] point out the difficulty in predicting error performance in the testing of nuclear power plants whereby data is very limited or non existant. This is exactly the case for many military systems where the error events may be extremely rare but very costly when they do occur. For these situations, it is appropriate to develop models that best describe the erring process and use the, limited as it may be, data to estimate the parameters.

This report summarizes efforts aimed at increasing our abilities to quantify the human error performance in man-machine systems as it relates to system effectiveness. In particular, a framework is described for quantifying human errors and modeling the occurrence of human error events in a system.

Before the models are presented, a classification system for human errors is presented in Section 2. In Section 3, a general approach for modeling human errors as a Semi-Markov Process is given with details for the special case of a two-state renewal model. These models enable one to relate the time-between-errors (TBE) to the time between decision points. It turns out that under suitable conditions the limiting distribution for the time between errors is exponential. A discussion with some concluding remarks is given in Section 4.

2. CLASSIFYING HUMAN ERROR

The fundamental problem in evaluating man-machine systems is to identify those factors affecting performance and to what extent they contribute to the overall effectiveness of the system. In any man-machine system sensory, information processing and decision, storage, and action functions must be performed (McCormick [12]). The responsibilities for these functions are allocated among the various human and machine elements and the overall system performance is dependent upon both the timeliness and the accuracy of each element. Through these functions and the interactions among man and machine elements, there are many ways in which the human operator can commit errors in performing a task. However, only those error activities that actually generate an effect on overall system performance are considered errors. Various attempts have been made to devise a classification system that will exhaust all means of human erring and is acceptable to everyone. These systems categorize errors in terms of the conscious and behavioral levels of the operator (Rook [18]), resulting mishaps and action types (Altman [4]), and task or element criticality (Pickrel and McDonald [16]). As an alternative to these systems, a proposed approach to classifying errors is to categorize tasks according to the underlying probabilistic structures that account for the uncertainties involved and hence contribute to error events.

We consider a man-machine system task comprising a human element who operates to achieve some prescribed mission or purpose. The intrinsic uncertainty involved in such a task is very complex, but for our purposes we shall consider the observable human uncertainty involved in the performance. Human uncertainty may be thought to

consist of choice and temporal components. Let τ represent a decision point at which the operator is required to perform action A. Figure 1 shows a sample realization of an operator's performance where A has outcomes a_1, a_2, ..., a_L occuring at decision points τ_1, τ_2, ...

Figure 1: Sample realization of operator performance.

This {X, τ} process establishes a conceptual basis for classifying tasks according to the relative complexity of the decision processes and time. A broad classification scheme is summarized in Table 1.

Table 1
DECISION CLASSES

Decision class	Decision Points τ_j: j=1, 2, ...	Actions a_i: i=1, ..., L
1	deterministic	random
2	random	deterministic
3	random	random

For the Class-1 decisions, an operator is required at each τ_j to perform an action a_i that is prescribed by some underlying probability distribution. Examples of these decisions arise in industrial inspection and sorting operations where the operators serve or interact with assembly lines. As an example, suppose a line inspector receives a particular sub-assembly component at a fixed rate of v units per hour and each unit is to be checked at m points for possible defect or flaw. So in Figure 1, the maximum number of actions is $L = 2^m$ and the inter-decision point times, $\tau_j - \tau_{j-1}$, are constant for all $j = 1, 2, \ldots$. The usual measure of effectiveness for industrial systems of this type is expected cost per unit. This clearly will depend highly upon the error performance of the operator and the associated costs.

In military systems, a more common type of decision problem is the Class-2. Here the inter-decision point times are random, but the particular actions to be performed are assumed to be known precisely to the operator. Examples of this category of decision problems are found in control monitoring tasks, typically of the vigilance type where the operator spends a disproportionate amount of time monitoring or awaiting for a decision point to occur. Many of the computerized tracking functions for large scale communication and data systems, e.g. the Navy Tactical Data System (NTDS), can be classified and analyzed as Class-2 decisions since the monitoring and control functions are human elements.

Class-3 decision tasks are of course very common in man-machine systems and particularly in the military command-control-and-communication systems. Here both a_i and τ_j are random events and hence the operator is uncertain both to which action will be required and to the time of the decision point. This is indeed the most difficult

class of decision problems in terms of analyzing and understanding man-machine system activities. There are more sources of potential human error due to increases numbers and complexities of interactions and man-machine linkages. Class-3, and to lesser extents Classes - 1 and 2 tasks require further within class categorizations.

3. CONSTANT ERROR PROBABILITY MODELS

The classification of tasks in accordance with the stochastic nature of the $\{X, \tau\}$ process provides an intuitive framework for developing quantitative indices for system performance. Many times the errors pertaining to system performance are rare events that generate large costs when they occur. So with limited data, it is difficult to gain a thorough understanding of the errors using rigorous statistical procedures, based on large samples, but the need for predicting performance and examining consequences is very important. For much circumstances, it is appropriate to use models for describing and studying performance and the effects on system effectiveness for given conditions on the $\{X, \tau\}$ process.

3.1 A Semi-Markov Formulation

We now consider a general formulation of the error process in a man-machine system. Assume a simple task with a single man-machine linkage and let the decisions be of the Class-2 type in Table 1. For time $t \geq 0$ we denote Z_t the system error state with state space Ω containing the set of all possible errors for the given system including 0. For our purpose here, consider the basic error classification scheme by Altman [4] whereby Ω shall be partitioned into the subsets 0 and

$\Omega_1 \equiv$ time violations

$\Omega_2 \equiv$ omissions

$\Omega_3 \equiv$ sequential errors

$\Omega_4 \equiv$ decision errors

For convenience, we require that the Ω_i's are mutually exclusive.

A typical realization of Z_t is shown in Figure 2. Conceptually, transitions among the error states occur in two stages.

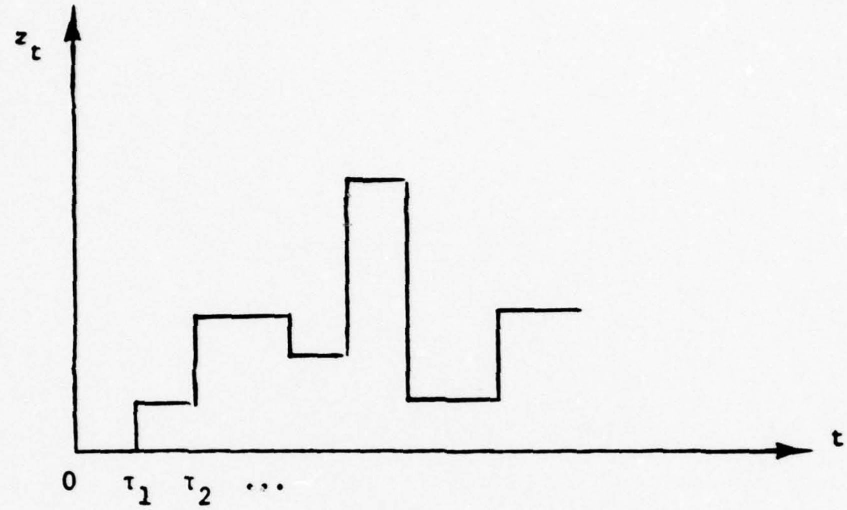


Figure 2: Sample Record of Error Performance

At each decision point τ_i, a choice of entry to the next state is made. The process then accumulates a time-to-transition in accordance with some distribuiton that is dependent upon the particular states involved. So letting N_i (t) represent the number of errors of type i in (0, t], we have the vector

$$N(t) = (N_0(t), \ldots, N_4(t)).$$

We shall assume that the decision points τ_j correspond to imbedding points for a Markov Chain that describes the state occurences immediately following transitions j=1, 2, ... Thus, the stochastic process $\{N(t): t \geq 0\}$ that counts errors is a Markov Renewal Process and $\{Z_t: t \geq 0\}$ that records the state of the process over time is a Semi-Markov Process. Knowledge of $\{N(t): t \geq 0\}$, along with the initial state of the process is sufficient for determining Z_t. However; in order to completely describe the process $\{Z_t: t \geq 0\}$ for a given

system it is necessary to know both the distributions for making transitions among the error states and the related distributions for holding times among states.

3.2 Two-State Renewal Models

As a special case of the general model described in Section 3.1, we shall consider the simple human error model for which there are only two states, $\Omega = \{0, 1\}$ and the decision times form a renewal process. Thus, any type of error is considered to be an "error event" with $\omega = 1$. We consider a work task involving decisions of Class 1 or Class 2 with interdecision point times $X_i = \tau_i - \tau_{i-1}$, $i = 1, 2, \ldots$, and $\tau_o \equiv 0$. At each decision point, τ_i, a human error is committed with probability $p > 0$ that is constant for each $i = 1, 2, \ldots$. Let y_j represent the time between errors $j-1$ and j, as shown in Figure 3.

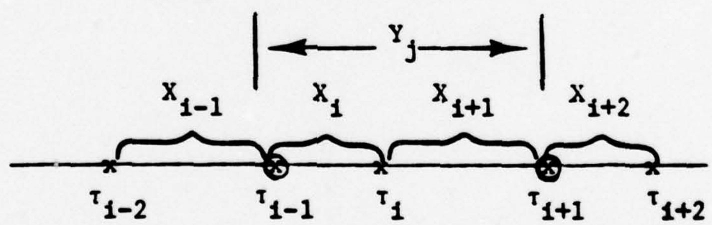


Figure 3: A Typical Realization of Event Times.

We shall further assume that the X_i's are independent and identically distributed F with $EX = \mu < \infty$. It then follows that the Y_j's are independent and identically distributed G. Letting their respective counting processes be represented by $\{N(t): t \geq 0\}$ and $\{N_e(t): t \geq 0\}$ we have for a fixed t

$$P\{N_e(t) = m\} = \sum_{n=m}^{\infty} P\{N_e(t) = m/N(t) = n\}P\{N(t) = m\} \qquad (1)$$

$$= \sum_{k=0}^{\infty} \binom{m+k}{m} p^m q^k P\{N(t) = m + k\}, \; p + q = 1.$$

In order to derive an expression for the distribution G of the time between errors, we note that random variable $Y > t$ if and only if $N_e(t) = 0$. It therefore follows from basic renewal theory that

$$P\{Y > t\} = \sum_{k=0}^{\infty} q^k \left[F_k(t) - F_{k+1}(t)\right] \qquad (2)$$

where F_k is the k-fold convolution of F with itself. Letting $\bar{g}(s)$ and $\bar{f}(s)$ denote the Laplace-Steiljes transforms of dG and dF, respectively, and transforming (2)

$$\int_0^{\infty} e^{-st} P\{Y > t\}dt = \sum_{k=0}^{\infty} q^k \int_0^{\infty} e^{-st} \left[F_k(t) - F_{k+1}(t)\right]dt$$

or

$$\frac{1}{s}(1-\bar{g}(s)) = \frac{1 - \bar{f}(s)}{s[1-q\bar{f}(s)]}, \; R_e(s) > 0$$

which simplifies to

$$\bar{g}(s) = \frac{p\bar{f}(s)}{1-q\bar{f}(s)}. \qquad (3)$$

This then provides us with a transform relationship between

the distributions associated with the times between errors and the times between decision points. From (3) we obtain expressions for the mean and variance of the time between errors directly,

$$E(Y) = \frac{1}{p}\ E(X)$$
$$\mathrm{Var}(Y) = \frac{1}{p^2}\left[p\ \mathrm{Var}(X) = qE^2(X)\right]. \quad (4)$$

Exponential Interdecision Times

One important special case of equation (3) is the situation that arises for the commonly assumed exponential interevent time distribution. It follows that G is exponential if and only if F is exponential. This is easily seem in (3) since for $F(x) = 1\text{-}e^{-x/\mu}$

$$\bar{f}(s) = \frac{1}{1+\mu s} \quad (5a)$$

hence

$$\bar{g}(s) = \frac{p}{p+\mu s} \quad (5b)$$

and inversion yields

$$g(t) = \frac{p}{\mu}e^{-\frac{p}{\mu}t},\ t \geq 0 \quad (5c)$$

Similarly, one can solve for $\bar{f}(s)$ given $\bar{g}(s)$ for the exponential to arrive at the exponential for the interdecision times, X, from the other direction. The popularity of this special case is due in part to the lack of memory characteristic of the exponential, suggesting a degree of conversatism when one must assume a distribution. The primary reason for this popularity, however, is due no doubt to the analytical convenience provided.

Normal Interdecision Times

In many systems the interdecision times are treated as Normally distributed random variables. This is only valid for those cases where the mean time between decision points, μ, is several standard deviations from the origin soas to insure that the probability of a negative time between decisions is approximately zero. A more general representation of these times and indeed adequate for many practical situations is the truncated Normal distribution

$$F(x) = \frac{\Phi(\frac{x-\mu}{\sigma})}{\Phi(\frac{\mu-\xi}{\sigma})}, \quad \xi < x < \infty \tag{6a}$$

where

$$\Phi(x) = \int_{-\infty}^{x} e^{-x^2/2} \frac{dx}{\sqrt{2\pi}}$$

and ξ is the point of truncation (i.e. no interdecision time can be of length less than ξ). It follows that the Leplace transform for the probability density function associated with (6a) is

$$\bar{f}(s) = \frac{\Phi\left(\frac{\mu-\sigma^2 s}{\sigma}\right)}{\Phi(\frac{\mu-\xi}{\sigma})} e^{-\mu s + \frac{1}{2}\sigma^2 s^2} \tag{6b}$$

from which it follows from (3) that

$$\bar{g}(s) = \frac{p\Phi\left(\frac{\mu-\sigma^2 s}{\sigma}\right)e^{-\mu s + \frac{1}{2}\sigma^2 s^2}}{\Phi(\frac{\mu-\xi}{\sigma})-q\Phi(\frac{\mu-\sigma^2 s}{\sigma})e^{-\mu s + \frac{1}{2}\sigma^2 s^2}} \tag{6c}$$

While the 2-state renewal models are simple in concept, the resulting human error distributions can be difficult to determine. This is evidenced by the result of (6), for the truncated Normal interdecision time distribution which arises commonly in practice. One approach to finding results for this case is to apply numerical inversion techniques. Another approach is to seek an adequate approximation for error times, given a general form of X.

3.3 A Limiting Result for the Time-Between-Errors

Let X and Y have distributions F and G, respectively, as previously defined. We shall require that $EX = \mu < \infty$ and define a random variable $Z = kY$ and designate its distribution by H. It follows from equation (3) that for $k > 0$,

$$\bar{h}(s) = \frac{1}{k}\,\bar{g}\left(\frac{s}{k}\right) \tag{7}$$

Using assymptotic arguments for small $p \to p_*$ while $\bar{f}(s) \to 1-\mu s + O(\mu s)$, from Equation (1),

$$\bar{h}(s) \to \bar{h}_o(s) = \frac{p(1-\frac{s\mu}{k})}{pk + q\mu s}$$

so with appropriate normalization

$$\bar{H}_*(s) = \bar{H}_o(s) + \frac{p}{k\mu s} \tag{8}$$

from which it follows that an approximate distribution for Z is given by

$$H_*(z) = 1 - e^{-\frac{pz}{q^2\mu}},\ z \geq 0. \tag{9}$$

3.4 An Application to Experimental Data

As a demonstration of the limiting result of Section 3.3 for time-between-errors, we shall apply the approximate TBE destribution of equation (9) to some experimental data derived from a study by Thomas [22]. In that study the objective was to examine the uncertainty effects on performance of operators conducting repetitively a sequence of manual operations containing a choice reaction element. This was a self-paced decision-making task of the Class-1 type, indicated in Table 1. A detailed description of the task and related experiment is reported elsewhere (see Thomas [22]), but a flow diagram showing the elemental breakdown for the task is given in Figure 4.

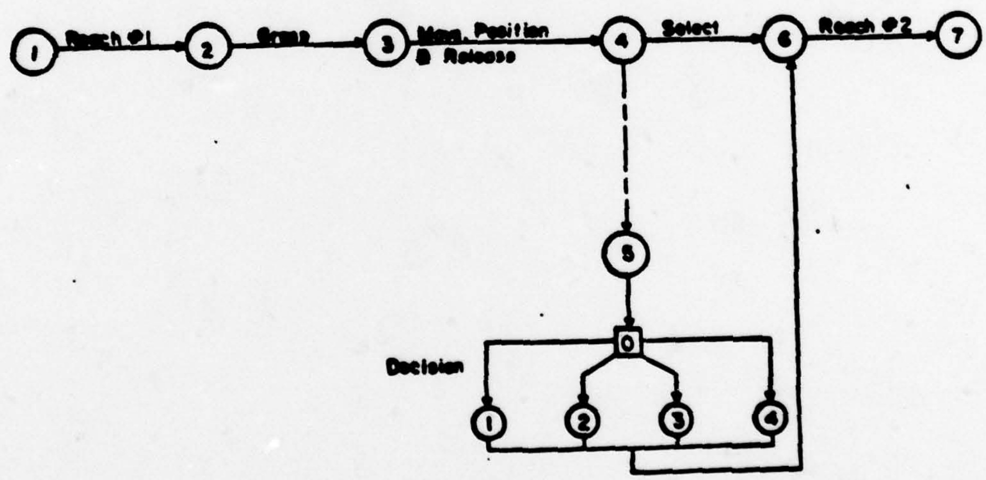


Figure 4: Laboratory Task Node Diagram

The nodes in Figure 4 correspond to distinct breakpoints in the task so as to enable one to take measurements of the performance for each segment of the operation. There were five operators each of which performed the task for twelve 1000 cycle duration sessions beyond several training trials. Although as seen from Figure 4 there were several modes of error in the task; for our purposes here, any error was considered as an error event.

Table 2 gives a summary of the error performance of three, of the five, operators.

Table 2

Error Performance for Experimental Task Operator

	1	2	3	Avg
$\hat{p}$	.048	.063	.041	.051
$\hat{\mu}_x$ msec	2213	2283	2482	2326
$\hat{\sigma}_x$ msec	164	304	255	248

The operators compared relatively well in performance with a average time between errors of 2326 msec and an average error probability of .051.

Figure 5 shows the fitted TBE distributions for the actual experimental data $\hat{E}_y(t)$ and the approximation of (9) $\hat{H}_*(t)$.

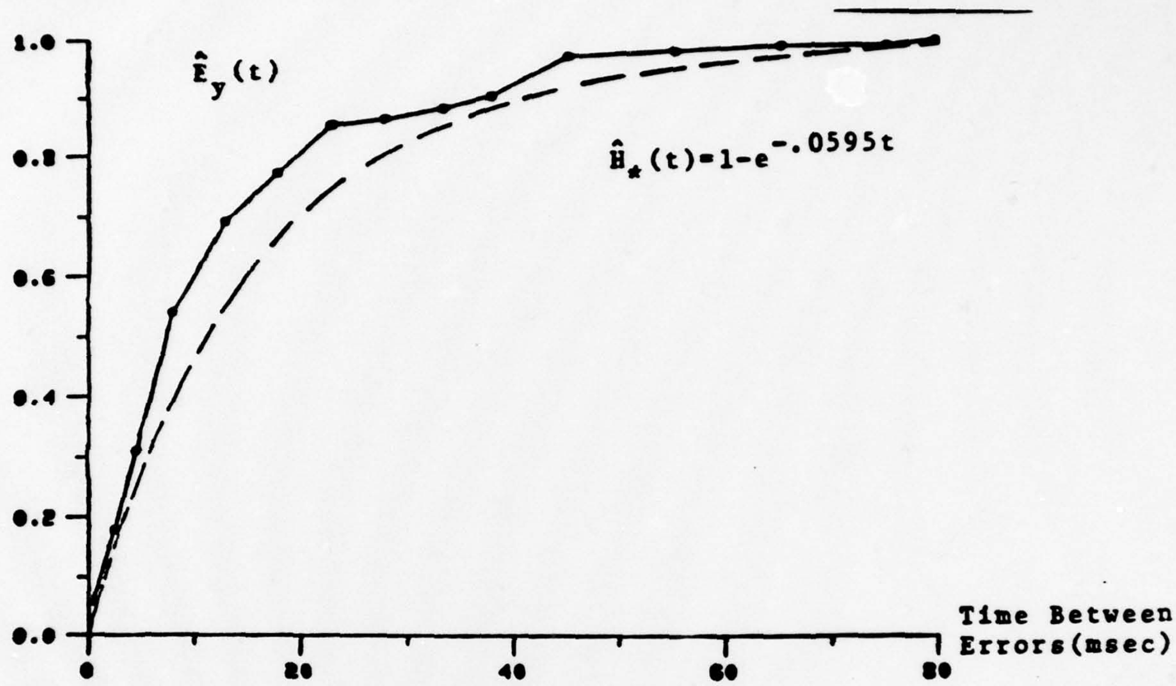


Figure 5: Comparison of Limiting Error Distribution to Experimental Data

As noted in Figure 5, the approximation overestimated the time-between-errors for a fixed probability throughout the sample data. None-the-less, the approximation does provide a reasonable comparison to the data.

4. CONCLUDING REMARKS AND DISCUSSION

The overall need for increasing our understanding of human errors is motivated by two main reasons. The first is safety and accident prevention. PL 91-596 of 1970 stipulates safety responsiblilities in the design of new systems which translates to minimum error performance in a man-machine system setting. Moreover, with the more responsible role of the human operator in modern man-machine systems of today, the consequence of an error can be much more serious and threatening to the welfare of people. A second pressing need for greater understanding in the human erring processes is to enable us to more realistically and accurately assess system effectiveness. Both system improvement and the development and design of new systems involve making comparisons among alternative systems or designs. Each man-machine linkage involving events that can affect the mission of the system must be determined and analyzed. Obviously, the accuracy of the overall MOE can be no greater than the contributing component performance measures. Typically, one or more of these components are highly succeptible to human errors.

The classification system presented in Section 2 is an approach that can be used to simplify the procedures for quantifying human error performance. It is also a convenient means for identifying and relating previous studies to a particular system and consolidating results into a framework. Psychologists have explored aspects of the Class-1 decision problem through choice reaction time studies (see Teichner and Krebs [21] and Smith[22] for reviews). The Class-2 decision problems have also been explored to an extent, in the laboratory setting, through vigilance studies (Mackworth [11]). Except for a few

eluded to cases (Carbonell [5], Carbonell et al [6], and Rouse [17]). the Class-3 problems have not been explored formally. Indeed; from an effectiveness viewpoint one would attempt to convert through work design and methods improvement Class-3 tasks into Class-1 or Class-2, thus providing little motivation for researchers to study this class. Still, there are many systems for which it is necessary to maintain task performance for Class-3. This classification system can of course be extended to include more refined categories (e.g. discrete time, continuous time, etc.).

The semi-Markov model, of Section 3.1, also offers a good structure for providing physical interpretations. Certain task and environmental conditions will result in patterns which lead to functions on Ω that typify such situations. For example; for the special case where the holding times (i.e. time spent in a particular error state before going to another) are Geometric distributed, $\{Z_t : t \geq 0\}$ is a Markov Chain. Further, under certain conditions (Thomas and Barr [23]) one can combine partitions in Ω to form a smaller chain that retains the Markov structure. A similar synthesis can be applied to the more general Semi-Markov Chain (Sertozo [19]), but further work on refinements is needed in this area. These approaches of taking functions on Ω that partition off similar transitory relationships show great promise for examining and further categorizing behavioral characteristics of man-machine linkages in general.

In this study we allowed the interdecision times X_i to be continuous random variables. It is easily shown that proceeding from equation (2), the discrete analog to equation (3) is

$$G(z) = \frac{pF(z)}{1-gF(z)} \qquad (10)$$

Where G(Z) and F(Z) are the probability generating functions associated with Y and X respectively. One can further develop, without difficulty, the discrete analog to the approximation for the TBE distribution of equation (9). The comparisons between this approximation and the experimental TBE distributions in Section 3.4 are relatively close. The major advantage of this result, however, is the fact that it is based on very broad and general assumptions that do not require an assumed distribution for the interdecision times X.

For command, control, and communication system environments, there are three major difficulties in providing adequate models for describing and predicting human error. First, we still have the general lack of understanding of human error characteristics in man-machine linkages. This problem will no doubt prevail for quite some time. Secondly, we are in need of model development that will capture the salient features of the physical system being modeled and incorporate the appropriate analytical and parametric details for representing the randomness. While the Semi-Markov model of Section 3 is general, more applications will provide needed experience on particular systems and characteristics that will promote further exploration of this general framework for modeling human error. Natural extensions of the renewal model, of Section 3.2, are to include three or more states and to allow the probabilities of errors at each decision point to be non-constant. The third major problem area is data availability. This problem motivated the development of the approximation of Section 3.3. There is a general lack of data on errors

and there will always be a lack of sufficient data for the catastrophic type errors involving very high costs or perhaps human life. In view of this, it is very reasonable to devote major efforts to identifying models and rationale for assuming distributions or even processes for representing error performance in complex man-machine systems. For this reason, a recommended direction for future work in this area is to develop a man-machine loop simulation model. These models have been developed in other areas (Alford and Buck [1]) where the man-machine linkages are extremely complex. A model should be tailored for the command, control, and communication environment.

REFERENCES

Alford, E. C. and Buck, J. R., "A Unit Task Simulator for the Evaluation of Interactive Man-Computer Systems," Purdue Lab. for Appl. Indust. Contr., Rep. No. 81, Purdue University, December, 1976.

Apostolakis, G. E. and Bansal, P. O., "Effect of Human Error on the Availability of Periodically Inspected Redundant Systems," IEEE Trans. on Reliability, Vol. R-26, pp. 220-225, 1977.

Adkren, W. B. and Regulinski, T. L., "Quantifying Human Performance for Reliability Analysis of Systems," Human Factors, Vol. 11, pp. 393-396, 1969

Altman, J. W., "Classification of Human Error," in W. B. Askren (ed.) Symposium on Reliability of Human Performance in Work, AMRL, TR. 67-88, May 1967.

Carbonnel, J. R., "A Queueing Model of Many-Instrument Visual Sampling," IEEE Trans. on Human Factors in Electronics, Vol. HFE-7, pp. 157-164, 1966.

Carbonell, J. R., Ward, J. L., and Sanders, J. W., "A Queueing Model of Visual Sampling Experimental Validation," IEEE Trans. on Man-Machine Systems, Vol. MMS-9, pp. 82-87, 1968.

Cooper, J. I., "Human-initiated Failures and Malfunction Reporting," IRE Trans. in Human Factors in Electronics, Vol. HFE pp. 104-109, 1961

Dunlay, W. J., Jr. and Horonjeff, R., "Application of Human Factors Data to Estimating Air Traffic Control Conflicts," Transpn. Res., Vol. 8, pp. 205-217, 1974.

Feyock, S., "Transition Diagram-Based CAI/HELP Systems," Int. J. Man-Machine Studies, Vol. 9, pp. 399-413, 1977.

Lamb, J. C. and Williams, K. E., "Prediction of Operator Performance for Sonar Maintenance," IEEE Trans. on Reliability, Vol. R-22, pp. 131-134, 1973.

Mackworth, N. H., "Researches on the Measurement of Human Performance," in Selected Papers on Human Factors in the Design and Use of Control Systems (ed., H. W. Sinaiko), Dover Publications, New York, pp. 174-331, 1961

McCormick, E. J., Human Factors Engineering, McGraw Hill, Ch. 1, 1970

References (cont.)

Meister, D., "The Problem of Human Initiated Failures," Proc., 8th Nat'l Symposium on Reliability and Quality Control, Washington, D. C., January 9-12, pp. 234-239, 1962.

Meister, D., "Development of Human Reliability Indices," Proc., Symposium on Human Performance Quantification in Systems Effectiveness, Naval Material Command, Washington, D. C., 1967.

Mills, R. G. and Hatfield, S. A., "Sequential Task Performance: Task Module Relationships, Reliabilities, and Times," Human Factors, Vol. 16, pp. 117-128, 1974

Pickrel, E. W. and McDonald, T. A., "Quantification of Human Performance in Large, Complex Systems," Human Factors, Vol. 6, pp. 647-663, 1964

Rouse, W. B., "Human-Computer Interaction in Multi-task Situations," IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-7, pp. 384-392, 1977.

Rook, L. W., Jr., "Reduction of Human Error in Industrial Production," Sandia Corporation, Albuquerque, N. M. SCTM 93-62(14), 1962.

Serfozo, R. F., "Functions of Semi-Markov Processes", SIAM J. Appl. Math., Vol. 20, pp. 530-535, 1971.

Smith, E. E., "Choice Reaction Time: An Analysis of the Major Theoretical Positions," Psychological Bulletin, Vol. 69, pp. 77-110, 1968

Teichner, W. H. and Krebs, M. J. "Laws of Visual Choice Reaction Time," Psychological Review, Vol. 81, pp. 75-98, 1974

Thomas, M. U., "A Human Response Model of a Combined Manual and Decision Task," IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-3, pp. 478-484, 1973.

Thomas, M. U. and Barr, D. R., "An Approximate Test of Markov Chain Lumpability," J. Am. Statistical Assoc., Vol. 72, pp. 175-179, 1977